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Analysis of Logistic Regression Regularization in Wild Elephant Classification with VGG-16 Feature Extraction

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ABSTRACT

The research article explores the intersection of image-based wildlife classification and logistic regression regularization, focusing on the classification of wild elephant species. It begins by highlighting the significance of ecological research in biodiversity monitoring and conservation and introduces Convolutional Neural Networks (CNNs) as potent tools for feature extraction from images. The VGG-16 model is particularly emphasized for its ability to capture hierarchical representations of visual features crucial for classification tasks. The integration of VGG-16 feature extraction with logistic regression regularization is proposed as a compelling approach, offering a balance between sophisticated feature representation and efficient classification algorithms. The literature review delves into image-based wildlife classification, emphasizing the role of CNNs, especially VGG-16, in extracting discriminative features. It discusses the fusion of VGG-16 features with logistic regression and the challenges in this field, such as dataset annotation and environmental variability. The method section outlines the dataset acquisition, feature extraction using the VGG-16 architecture, and model configuration using logistic regression with lasso and ridge regularization. The process of finding the optimal regularization parameter (lambda) and model evaluation through cross-validation is detailed. Results showcase the optimal lambda values for lasso and ridge regularization and compare the performance of logistic lasso and logistic ridge models. Misclassification analysis reveals factors influencing classification accuracy, including feature variability and contextual complexity. The discussion reflects on the implications of the findings, emphasizing the importance of lambda selection and addressing challenges in wildlife classification. It suggests avenues for further research, such as advanced modeling techniques and feature engineering approaches. In conclusion, the study contributes to advancing wildlife classification efforts by leveraging state-of-the-art techniques and sheds light on opportunities to enhance classification accuracy in wildlife conservation.

Keywords: Wildlife Classification; Logistic Regression; VGG-16; Lasso Regularization; Ridge Regularization

INTRODUCTION

In the realm of ecological research, the classification of wildlife species through image analysis stands as a crucial endeavor, offering profound insights into biodiversity monitoring and conservation efforts (Chisom et al., 2024). Leveraging advancements in computer vision and machine learning techniques, researchers have developed sophisticated methodologies for species identification and classification based on images captured in their natural habitats (Dhanya et al., 2022). This introduction encapsulates the essence of the research article's sections, which delve into various aspects of image-based wildlife classification and the utilization of logistic regression regularization in conjunction with VGG-16 feature extraction for classifying wild elephant species.

Image-based wildlife classification has witnessed remarkable progress, driven by the emergence of Convolutional Neural Networks (CNNs) as a potent tool for feature extraction from images (Battu & Reddy Lakshmi, 2023). Among these architectures, the VGG-16 model has garnered significant attention for its efficacy in capturing intricate features vital for classification tasks (Handayani, Rosnelly, & Hartono, 2023). By traversing through its deep layers, VGG-16 can discern hierarchical representations of visual features, ranging from low-level textures to high-level object semantics, enabling robust species identification and monitoring (Firmansyah & Rosnelly, 2023).

The fusion of VGG-16 feature extraction with logistic regression presents a compelling approach in wildlife classification (Rajabizadeh & Rezghi, 2021). Logistic regression, renowned for its simplicity and efficiency, complements the rich feature representation extracted by VGG-16, offering a balance between sophisticated feature representation and efficient classification algorithms (Samudra, Rosnelly, Situmorang, & Ramadhan, 2023). Furthermore, regularization techniques such as lasso and ridge regularization play a crucial role in enhancing the

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generalization performance of logistic regression models, ensuring reliable classification outcomes amidst challenges like overfitting and feature complexity (Kumar, Kedam, Sharma, Mehta, & Caloiero, 2023).

The research article navigates through the integration of VGG-16 feature extraction with logistic regression regularization, aiming to classify wild elephant species based on extracted image features. Through meticulous dataset curation, feature extraction, model training, and evaluation, the study provides insights into the optimal regularization parameters and model performance, shedding light on the complexities and opportunities in image-based wildlife classification. Overall, the research article contributes to advancing wildlife classification efforts by leveraging state-of-the-art techniques in feature extraction and classification algorithms. By elucidating the interplay between VGG-16 feature extraction, logistic regression regularization, and wildlife classification, the study paves the way for enhanced biodiversity monitoring, conservation initiatives, and ecological research.

LITERATURE REVIEW

Image-based wild life classification

The classification of wildlife species through image analysis has emerged as a crucial aspect of ecological research, offering invaluable insights into biodiversity monitoring and conservation efforts (Ukwuoma et al., 2022). Leveraging advancements in computer vision and machine learning techniques, researchers have developed sophisticated methodologies for species identification and classification based on images captured in their natural habitats (Saleh, Sheaves, & Rahimi Azghadi, 2022).

One prevalent approach in image-based wildlife classification involves the extraction of discriminative features from images using Convolutional Neural Networks (CNNs) (Ng, Connie, Choo, & Goh, 2022). Among these architectures, the VGG-16 model stands out for its effectiveness in capturing intricate features from images. With its deep architecture comprising 16 layers, including convolutional and fully connected layers, VGG-16 can learn hierarchical representations of visual features, ranging from low-level features like edges and textures to high-level features corresponding to object shapes and semantics (Margolang, Riyadi, Rosnelly, & Wanayumini, 2023).

CNN-based approaches have played a pivotal role in various wildlife classification endeavors, enabling researchers to identify individual species and monitor population dynamics across different habitats. For instance, studies have utilized CNNs to distinguish between different species of birds (Dharaniya R, Preetha M, & Yashmi S, 2022), mammals (Faizal & Sundaresan, 2022), and marine life (Fawwaz, Yennimar, Dharsinni, & Wijaya, 2023), facilitating efficient species monitoring and conservation efforts. Additionally, CNNs have been deployed in habitat monitoring applications (Pérez-Carabaza, Boydell, & O'Connell, 2021), aiding in detecting changes in ecosystems (Burrewar, Haque, & Haider, 2024) and assessing the impact of environmental factors on wildlife populations (Norman et al., 2023).

Despite significant advancements, challenges remain in image-based wildlife classification. These include the need for annotated datasets encompassing diverse species and habitats (Rubbens et al., 2023), addressing class imbalance issues (Bria, Marrocco, & Tortorella, 2020), and mitigating the impact of environmental variables on image quality and feature extraction (Roberts, Helmholz, Parnum, & Krishna, 2023). Additionally, ensuring the interpretability of CNN-based models and their ability to generalize across different environmental conditions warrant further investigation to ensure reliable and transferable classification outcomes.

VGG-16 Feature Extraction in Classification

In recent years, the utilization of deep learning models, particularly Convolutional Neural Networks (CNNs), for feature extraction in classification tasks has garnered significant attention across various domains, including wildlife classification (de Silva et al., 2022). Among these architectures, the VGG-16 model has emerged as a standout choice for its effectiveness in capturing intricate features from images (Hindarto, Afarini, & Esthi H, 2023).

The VGG-16 architecture, characterized by its deep structure comprising 16 layers, including convolutional and fully connected layers, enables it to learn hierarchical representations of visual features (Al-Khater & Al-Madeed, 2024). Starting from low-level features like edges and textures to high-level features corresponding to object shapes and semantics, VGG-16 can extract discriminative features that are crucial for classification tasks (Ye et al., 2021).

In the realm of image classification, researchers have leveraged VGG-16 for a myriad of tasks, including object recognition (PARDEDE & HARDIANSAH, 2022), scene understanding (Masood, Ahsan, Munawwar, Rizvi, & Ahmed, 2020), fine-grained categorization (Cao et al., 2024), and wildlife identification (Islam, Khan, Abedin, Habibullah, & Das, 2019). Moreover, VGG-16 features have been extensively used as a basis for transfer learning, where pre-trained models are employed as feature extractors for downstream classification tasks (Pardede, Sitohang, Akbar, & Khodra, 2021). By leveraging the knowledge learned from large-scale datasets like ImageNet, VGG-16

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features can be fine-tuned or utilized directly to classify images in specialized domains with limited training data, yielding superior performance compared to training models from scratch.

However, challenges exist in deploying VGG-16 for feature extraction, including computational complexity, memory requirements, and the need for large-scale annotated datasets for training (Alzubaidi et al., 2021). Additionally, the interpretability of features extracted by VGG-16 and their relevance to specific classification tasks remain areas of ongoing research.

Combination of VGG-16 and Logistic Regression

The fusion of VGG-16 feature extraction with logistic regression presents a compelling approach in the realm of wildlife classification, offering a balance between sophisticated feature representation and efficient classification algorithms (Tambunan, Rosnelly, & Situmorang, 2023).

In recent studies, researchers have explored the integration of VGG-16 features with logistic regression to classify wildlife species based on image features. This approach has shown promising results in identifying individual species, monitoring population dynamics, and facilitating conservation efforts (Hooten, Lu, Garlick, & Powell, 2020; Hridayami, Putra, & Wibawa, 2019; Rismiyati & Luthfiarta, 2021).

Regularization techniques, such as lasso and ridge regularization, play a crucial role in mitigating overfitting and enhancing the generalization performance of logistic regression models. By tuning the regularization parameters, researchers can control the complexity of the model and improve its ability to generalize to unseen data (Qin & Lou, 2019).

In summary, the combination of VGG-16 feature extraction with logistic regression holds immense potential in advancing wildlife classification efforts. By harnessing the strengths of both approaches, researchers can achieve robust and interpretable classification outcomes, contributing to biodiversity monitoring, conservation initiatives, and ecological research. Continued research efforts focused on refining model architectures, optimizing regularization techniques, and addressing domain-specific challenges are essential for unlocking the full potential of this approach in wildlife classification.

METHOD

Dataset

The study utilizes a dataset comprising images of wild elephant species originating from Africa and Asia, procured through Google image searches. For data collection, we employed specific keywords, namely "Loxodonta africana" and "Loxodonta cyclotis," to retrieve images of African elephants, while "Elephas maximus" was utilized for sourcing images of Asian elephants. Each elephant species is represented by a total of 100 images, exemplified by samples depicted in Figure 1.

Fig 1. Dataset Sample

The extracted features from the 200 elephant images are utilized as the dataset for the subsequent processes, namely the determination of the optimal lambda value and the classification of elephant species. In determining the most optimal lambda value, the dataset is divided using an 80:20 sampling ratio, where 80% of the data is used as training data and 20% of the data is used as test data to determine the performance of each model.

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Feature Extraction

The study utilizes the VGG-16 architecture to extract features from the dataset of elephant images. VGG-16, a variant of convolutional network (ConvNet) architectures, integrates a combination of 32 and 64 filters in its convolutional layers (Tanuwijaya & Roseanne, 2021). The specific configuration of the VGG-16 architecture utilized in this study is depicted in Figure 2.

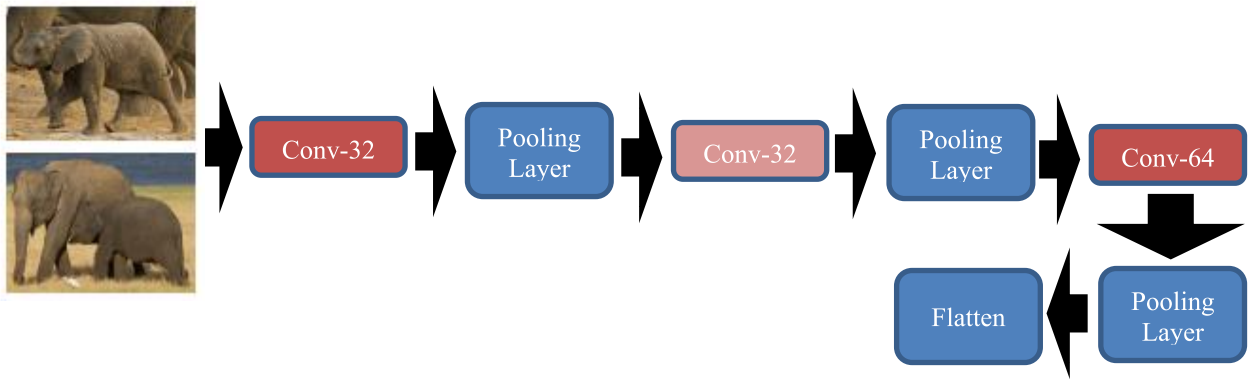

Fig 2. VGG-16 Architecture

Below is the explanation of the VGG-16 architecture depicted in Figure 2 above:

1. Input Image
   The input to the ConvNets is a fixed-size 224 × 224 RGB image, marking the initial input stage in the architecture.
2. Convolutional Layers
   Images are processed through a stack of convolutional layers with small receptive fields of 3 × 3, denoted as the Conv-32 and Conv-64 layers in the architecture.
3. Pooling Layers
   Spatial pooling is conducted via max-pooling layers, succeeding some convolutional layers. Max-pooling is executed over a 2 × 2 pixel window with a stride of 2, facilitating downsampling and feature retention.
4. Fully-Connected (FC) Layers
   Subsequent to the convolutional layers, three Fully-Connected (FC) layers are employed. The first two FC layers consist of 4096 channels each, signifying the Flatten step, wherein the output is flattened into a vector of 4096 dimensions.
5. Activation Function
   All hidden layers, encompassing convolutional and fully connected layers, are endowed with the rectification (ReLU) non-linearity. ReLU facilitates the introduction of non-linearity, aiding the network in learning intricate patterns and relationships within the data.

Model Configuration

The classification process of wild elephant species in this study utilizes the Logistic Regression algorithm, incorporating variations of lasso and ridge regularization. Logistic Regression is chosen for its simplicity, computational efficiency, capability to handle linear separability, regularization options, and probability estimation abilities, making it suitable for classification problems with image feature extraction datasets (Adeli, Li, Kwon, Zhang, & Pohl, 2020). In classifying African and Asian elephant species using a dataset consisting of 4096 image features extracted by VGG-16, the logistic regression algorithm fits a logistic function to the input features through the following steps:

1. Input Representation
   Initially, each image is represented by a vector of 4096 features obtained from the VGG-16 model, capturing various aspects and patterns learned during the convolutional and pooling layers of the VGG-16 architecture.
2. Probability Estimation
   Logistic regression estimates the probability of each elephant image belonging to either the African or Asian species. It accomplishes this by applying a linear combination of the input features, followed by passing the

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result through the logistic function, which maps the linear combination to a value between 0 and 1, representing the probability of the image belonging to a particular species.

3. Model Training
Labeled examples of elephant images are used to train the logistic regression model, which adjusts its parameters (coefficients) during the training process to minimize the difference between predicted probabilities and the actual labels of the training data.
4. Classification
Once trained, the logistic regression model classifies new images by computing the probability of each image belonging to the African or Asian species using the learned parameters. The image is then assigned to the species with the highest probability.

Regularization is crucial in logistic regression algorithms to prevent overfitting, where the model becomes overly complex and fails to generalize patterns to new data. Regularization controls the model's complexity and enhances performance on unseen test data. In this study, variations of lasso and ridge regularization are employed, utilizing the lasso regularization formula (1) and the ridge regularization formula (2) as follows (Kolluri, Kotte, Phridviraj, & Razia, 2020):

$$Cost(X, y, \theta) = -\frac{1}{m}\sum_{i=1}^{m}\left|y^i \log(h_0 X^i) + (1 - y^i)\log(1 - h_0 X^i)\right| + \lambda\sum_{j=1}^{n}\theta_j \quad (1)$$

$$Cost(X, y, \theta) = -\frac{1}{m}\sum_{i=1}^{m}\left|y^i \log(h_0 X^i) + (1 - y^i)\log(1 - h_0 X^i)\right| + \lambda\sum_{j=1}^{n}{\theta_j}^2 \quad (2)$$

where:

$Cost(X, y, \theta)$: the logistic regression cost function with lasso or ridge regularization
m : the number of training examples
n : the number of features
X^i : the matrix of input features
y^i : the vector of labels
θ_j : the vector of model parameters
$h_0 X^i$: the logistic function
λ : the regularization parameter

Various values of λ (0.05, 0.1, 0.5, 1, 2, and 3) are employed to determine the optimal parameters for each model. Each λ variation is utilized in the classification process using the training data, which is subsequently evaluated based on performance. The training data, obtained from an 80:20 sampling ratio, is utilized for the classification process, and the performance is evaluated using cross-validation techniques. The λ values yielding the best evaluations for each model are then utilized as the final parameters for each model in the subsequent classification process.

Model Evaluation

This study employs cross-validation method to evaluate the model, both in the process of finding the optimal lambda value and comparing the performance of lasso and ridge regularization in classifying elephant images. The metrics used are accuracy, precision, and recall, obtained from the calculation results of values in the confusion matrix table, using the following formulas (Riyadi, Hartono, & Wanayumini, 2023):

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad (3)$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (4)$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (5)$$

$$F1 = \frac{2\ X\ Precision\ X\ Recall}{Precision + Recall} \quad (6)$$

RESULTS

A. Best Lambda for Regularization

By utilizing 80% of the dataset as training data and variations of λ values at 0.05, 0.1, 0.5, 1, 2, and 3, the evaluation results of 10-fold cross-validation are obtained as shown in Table 1.

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Table 1. Performance Results With Various λ

λ	Model	Accuracy	Precision	Recall	F1
0.05	Logistic Lasso	0,500	0,333	0,250	0,500
	Logistic Ridge	0,825	0,825	0,826	0,825
0.1	Logistic Lasso	0,700	0,698	0,705	0,700
	Logistic Ridge	0,850	0,850	0,850	0,850
0.5	Logistic Lasso	0,800	0,800	0,801	0,800
	Logistic Ridge	0,875	0,875	0,875	0,875
1	Logistic Lasso	0,838	0,837	0,838	0,838
	Logistic Ridge	0,881	0,881	0,881	0,881
2	Logistic Lasso	0,856	0,856	0,856	0,856
	Logistic Ridge	0,888	0,888	0,888	0,888
3	Logistic Lasso	0,844	0,844	0,844	0,844
	Logistic Ridge	0,888	0,888	0,888	0,888

Based on the performance metrics observed in Table 1 for various λ values in logistic lasso and logistic ridge regularization, several patterns can be discerned. For logistic lasso regularization, the accuracy, precision, recall, and F1 score generally increase as the λ value increases from 0.05 to 1, reaching its peak at λ = 2, and then slightly decreases at λ = 3. This indicates that as the regularization strength increases, the model's generalization ability improves up to a certain point, after which further regularization might lead to some loss in performance. On the other hand, for logistic ridge regularization, the performance metrics exhibit a consistent and incremental improvement as the λ value increases from 0.05 to 3. This suggests that the regularization parameter effectively enhances the model's generalization ability without causing significant performance degradation.

Considering the performance results, the best λ value for logistic lasso regularization is λ = 2, where it achieves relatively high accuracy, precision, recall, and F1 score. For logistic ridge regularization, λ = 3 is the most optimal choice as it consistently yields the highest performance across all metrics without signs of overfitting. Overall, the choice of the best λ value depends on the trade-off between model complexity and generalization performance. λ values that strike a balance between these factors, such as 2 for logistic lasso and 3 for logistic ridge, are preferable as they provide robust performance while controlling for overfitting.

Models Performance

After obtaining the optimal λ values for each regularization (λ = 2 for lasso and λ = 3 for ridge), these values are utilized in each model to classify the VGG-16 feature extraction results. Table 2 shows the confusion matrix generated by both models in classifying the 200 elephant images.

Table 2
Confusion Matrix of Lasso and Ridge Regularization

Model	Actual	Predicted	
		African	Asian
Logistic Lasso	African	15	5
	Asian	6	14
Logistic Ridge	African	17	3
	Asian	5	15

Based on the confusion matrix results above, we observe the following:

1. Logistic Lasso Model

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Out of the 20 actual African elephant images, the model correctly predicted 15, while misclassifying 5 as Asian elephants. Similarly, out of the 20 actual Asian elephant images, the model correctly predicted 14, but misclassified 6 as African elephants.

2. Logistic Ridge Model
For the logistic ridge model, out of the 20 actual African elephant images, it correctly predicted 17, with 3 misclassifications as Asian elephants. Likewise, out of the 20 actual Asian elephant images, the model correctly predicted 15, but misclassified 5 as African elephants.

Both models show relatively similar performance in classifying African and Asian elephant images, with slight variations in the number of correct predictions and misclassifications. To further analyze the misclassified images from each model, Table 3 illustrates the distribution of actual and predicted labels for each misclassified class.

Table 3.Misclassified Class Feature Statistic

Actual	Predicted	Model	Image Name	Feature Statistics				
				Mean	Median	Dispersion	Min	Max
African	Asian	Logistic Lasso	84	0.485	0.204	126.353	0	394.917
			46	0.528	0.296	118.949	0	362.973
			71	0.493	0.221	123.798	0	357.961
			91	0.502	0.232	123.879	0	380.852
			19	0.519	0.25	122.518	0	371.414
		Logistis Ridge	84	0.485	0.204	126.353	0	394.917
			71	0.493	0.221	123.798	0	357.961
			91	0.502	0.232	123.879	0	380.852
Asian	African	Logistic Lasso	31	0.535	0.303	118.139	0	366.112
			21	0.479	0.205	126.416	0	415.546
			88	0.535	0.278	120.404	0	368.778
			80	0.506	0.235	123.907	0	371.055
			57	0.484	0.222	124.149	0	359.476
			16	0.501	0.244	122.548	0	391.343
		Logistis Ridge	21	0.479	0.205	126.416	0	415.546
			88	0.535	0.278	120.404	0	368.778
			57	0.484	0.222	124.149	0	359.476
			16	0.501	0.244	122.548	0	391.343
			60	0.451	0.152	129.721	0	368.038

Despite variations in feature statistics and image names, some patterns emerge. For instance, in the Logistic Lasso model, images 84, 71, and 91 were misclassified as Asian elephants, while images 21, 88, and 57 were misclassified as African elephants. These misclassifications suggest that certain images may possess ambiguous features or contextual cues that challenge the classification models. Similarly, in the Logistic Ridge model, images 21, 88, and 57 were also misclassified as African elephants, indicating consistent misclassification across different regularization techniques. Conversely, image 60 was misclassified as an Asian elephant in the Logistic Ridge model but not in the Logistic Lasso model, suggesting that this image may possess unique features that influence classification differently across models.

Upon further analysis of the misclassified images from both the Logistic Lasso and Logistic Ridge models, it's evident that the discrepancies between the actual and predicted labels may stem from various factors:

1. Feature Variability
The wide range of feature statistics across misclassified images indicates the diverse characteristics present in the dataset. These variations in features could lead to ambiguity in classification, making it challenging for the models to accurately distinguish between African and Asian elephants.
2. Contextual Complexity

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Some images may contain contextual cues or environmental factors that influence the classification process. For example, images captured in different habitats or lighting conditions may exhibit distinct features that are not effectively captured by the models.

3. Model Sensitivity
   The sensitivity of the logistic regression models to different feature patterns and regularization parameters could contribute to misclassifications. Certain images may possess subtle features that are difficult for the models to discern, leading to errors in prediction.
4. Sample Representation
   The distribution of samples across different elephant species and environmental conditions may not be evenly represented in the dataset. As a result, the models may not have sufficient training data to effectively learn and generalize the underlying patterns, leading to misclassifications.
5. Model Complexity
   The complexity of the logistic regression models, combined with the regularization techniques applied, may affect their ability to generalize to unseen data. Overly complex models may be prone to overfitting, while overly simplistic models may struggle to capture the intricacies of the dataset.

Overall, the misclassifications observed in both models highlight the complexities involved in classifying wild elephant species based on image features.

DISCUSSION

Optimum Lambda for Lasso and Ridge Regularization

The analysis of regularization parameter (λ) optimization in logistic lasso and logistic ridge regression reveals distinct patterns in model performance. For logistic lasso, as λ increases from 0.05 to 1, there is a noticeable improvement in accuracy, precision, recall, and F1 score, peaking at $\lambda = 2$, followed by a slight decline at $\lambda = 3$. This suggests that moderate regularization enhances the model's generalization ability, with $\lambda = 2$ striking an optimal balance between bias and variance. Conversely, logistic ridge regularization demonstrates consistent performance improvement with increasing λ values from 0.05 to 3, indicating effective regularization without significant performance degradation. The most optimal λ value for logistic ridge is found to be 3, offering high accuracy and stability across all metrics. These findings underscore the importance of λ selection in balancing model complexity and generalization performance. $\lambda = 2$ for logistic lasso and $\lambda = 3$ for logistic ridge emerge as robust choices, ensuring optimal performance while mitigating the risk of overfitting. Ultimately, the decision on the best λ value hinges on the specific trade-off between model complexity and predictive accuracy, with the identified λ values providing a solid foundation for achieving reliable and generalizable classification outcomes.

Misclassification Analysis

The performance evaluation of the logistic lasso and logistic ridge models, utilizing optimal regularization parameters ($\lambda = 2$ for lasso and $\lambda = 3$ for ridge), yielded insightful findings regarding their classification performance on VGG-16 feature extraction results of 200 elephant images. The confusion matrix analysis revealed similar performance between the two models, albeit with slight variations in correct predictions and misclassifications. Notably, both models exhibited a degree of misclassification, with logistic lasso misclassifying 11 images (5 African and 6 Asian elephants) and logistic ridge misclassifying 8 images (3 African and 5 Asian elephants). Further examination of misclassified images unveiled potential factors contributing to these discrepancies, including feature variability, contextual complexity, model sensitivity, sample representation, and model complexity. These findings underscore the multifaceted nature of wildlife classification based on image features, highlighting the need for robust model training, feature representation, and consideration of contextual factors to improve classification accuracy. Despite the challenges posed by these factors, the analysis provides valuable insights into the limitations and opportunities for enhancing the efficacy of classification models in wildlife conservation efforts.

CONCLUSION

The investigation into regularization parameter optimization and model performance in the classification of wildlife based on image features yielded valuable insights and implications for practical application and further research. In optimizing λ values for logistic lasso and logistic ridge regularization, $\lambda = 2$ emerged as the optimal choice for logistic lasso, striking a balance between model complexity and generalization performance, while $\lambda = 3$ proved to be the most effective for logistic ridge, ensuring high accuracy and stability across all metrics. These findings underscore the importance of λ selection in achieving robust classification outcomes, with λ values of 2 for logistic

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lasso and 3 for logistic ridge serving as reliable parameters for future model deployment. Additionally, the analysis of misclassification patterns revealed the multifaceted nature of wildlife classification, with factors such as feature variability, contextual complexity, model sensitivity, sample representation, and model complexity influencing classification accuracy. Despite these challenges, the study provides valuable insights into the complexities of wildlife classification and highlights avenues for improving model training, feature representation, and contextual consideration to enhance classification accuracy in wildlife conservation efforts. Moving forward, further research could explore advanced modeling techniques and feature engineering approaches to address the identified limitations and optimize classification performance in wildlife conservation applications.

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